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Modelling the effectiveness of climate policies: How important is loss aversion by consumers?

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ABSTRACTS

Reliable decarbonisation policies can only be developed with a thorough understanding of how consumers choose between energy technologies. Current energy models assume optimal consumer decisions which may result in expectations of the effectiveness of climate policies that are far too optimistic. Prospect Theory, on the other hand, aims to model real-life choices, based on empirical observations that losses have a relatively larger influence on decisions than gains, relative to a reference point. Here, we show for the first time how loss aversion can be included into a global energy model with high spatial resolution, using heating technology uptake as a case study. We simulate the future heating technology diffusion for 59 world regions covering the globe, with and without the consideration of loss aversion. We find that ignoring the implications of loss aversion overestimates the market uptake of renewables, in individual countries as well as on the global level. As a consequence, loss aversion results in higher projected CO_2 emissions by households, and the need for much stronger policy instruments for achieving decarbonisation targets. In the case of residential heating, a carbon tax of 200 €/tCO_2 is projected to reduce overall emission levels to a similar extent than a carbon tax of 100 €/tCO_2 without the consideration of loss aversion. Even for similar degrees of decarbonisation, accounting for loss aversion implies substantial changes in the underlying technology composition: technology choices become subject to a 'conservative shift' towards low-carbon technologies which are relatively less efficient, but already more established in local markets.

1. Introduction

The Paris Agreement aims at limiting global warming to well below 2 °C, which requires a rapid decarbonisation of the energy system worldwide [1]. Decarbonisation scenarios and policies aimed at the uptake of low-carbon technologies are usually analysed by means of energy models, either on their own or as part of larger ensembles (e.g., integrated assessment models) [2]. At their core, they describe how the technology composition of the energy system might change over time, and project the resulting influence on energy use and greenhouse gas (GHG) emissions.

Large-scale energy models are typically based on optimisation algorithms, which aim at identifying feasible pathways at the lowest overall system cost (given the specified constraints, such as a carbon budget) [3]. Underlying such algorithms are the assumptions of rational decision-making, in form of cost minimisation or utility maximisation, at the whole system level [4]. Such a method is arguably useful in a normative frame, as it enables to identify desirable and feasible system configurations. However, in a positive descriptive sense, it implies a view in which energy technologies are solely rationally chosen based on cost and performance characteristics by a social planner or representative agent, which is not how society works. In reality, technological change depends on the uncoordinated decisions of millions of people, who act according to their different individual needs and perceptions, and different types of biases compared to the normative frame [5].

In particular, behavioural research shows, with substantial amounts of empirics, that human decision-making systematically deviates from the rational choice assumptions as defined by classical economics [6–9]. This implies that the real-world impacts of decarbonisation policies on technology choices could be very different from what would be expected based on rational decision-making [10–12]. Where this matters most is in policy-making: how to ensure that technological change policy is

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successful, and that emissions targets are met? This is particularly relevant for policies aimed at energy end-use sectors, such as road transport or residential heating, where most decisions are made by consumers, whose behaviour is furthest from classical rational choice theory [13]. One of the key questions to be solved is how a more realistic representation of human behaviour in large-scale quantitative energy models can be achieved, to better inform a roll-out of successful GHG emission mitigation policies [14–17].

A well-established alternative to the prevalent assumptions of rational choice theory is Prospect Theory, which offers an empirically validated framework for describing how individuals make decisions in reality, independently of normative considerations of optimality [18–20]. For choices between consumption goods, the central element of Prospect Theory is loss aversion, which describes the observation that losses have a relatively larger impact on observed decisions than gains, relative to a subjective reference point [18–20]. On average, the impact of losses is found to be around twice as strong, compared to equally seized gains [21]. Following the classical experiments on loss aversion in product choice by Knetsch [22] and Kahneman et al. [23], this behavioural pattern was reported for consumer choices ranging from eggs [24] to real estate [25].

Loss aversion has not only been observed in human adults, but also for children [26], and even for capuchin monkeys [27,28]. Given its pervasiveness, this suggests that loss aversion might be an evolutionarily evolved cognitive strategy, and hence part of our neurological inheritance. Indeed, Tom et al. [29] described that the measured activity in involved brain regions is more sensitive to losses than to gains. One potential explanation is an evolutionary adaptation to survival-related challenges, resulting in an increased sensitivity to negative emotions such as fear and anxiety, and hence a bias against losses [29,30]. This points towards an evolutionarily hard-wired property of human behaviour, with critical importance for the effective design of energy and climate policies [10,31].

In the domain of energy, choice experiments in the USA and eight European countries indicate that loss-averse decision-makers are less likely to buy energy efficient technologies, such as alternative fuel vehicles and energy-efficient light bulbs [32,33]. The reason is that higher upfront costs are often evaluated as losses, which therefore have a relatively stronger impact on decisions than future energy savings (which are evaluated as gains). Similar effects of loss aversion on consumer preferences are reported for time-of-use electricity tariffs [34,35], gasoline demand [36], cars [37], and renewables [38,39]. Closest to our work, Safarzynska and van den Bergh [40] included loss aversion into a regression-based model of passenger car uptake in Germany, and showed that loss-averse consumers buy on average less fuel-efficient cars than rational agents. Knobloch and Mercure [11] suggested how loss aversion could be integrated into a basic choice model for energy technology uptake, and that this can predict more accurately observed energy efficiency investments by firms.

Still, despite the overwhelming empirical evidence, loss aversion has not yet been considered in any energy model which covers one or more countries. Here, we show how loss aversion can be included into a simulation model of heating technology uptake, FTT:Heat. This model's representation of technology uptake is strongly empirical, based on detailed regional datasets of consumer markets. It simulates future technology diffusion in 59 world regions covering the globe, which allows to analyse policy scenarios for individual countries as well as on the global level. Importantly, the technological trajectory is not based on economy-wide optimisation (to answer the question what *should* ideally happen), but on a dynamical bottom-up simulation of individual choices of heterogeneous agents with bounded rationality (to answer the question what *would* happen over time). As a dynamical simulation model, FTT:Heat is thus particularly well suited to account for real-world imperfections of human decision-making, such as loss aversion.

We contribute to the ongoing discussion on how to increase the behavioural realism of energy and integrated assessment models [41–44], which has so far neglected the possible influence of loss aversion. At the example of the residential heating sector, we analyse to which extent loss aversion influences model projections of technological change and the effectiveness of climate policies, both on the global level and on the level of individual countries. To evaluate the relevance of loss aversion, we simulate a current trends scenario and four decarbonisation policy scenarios, involving different levels of residential carbon taxes and subsidy payments. We show that loss aversion has important implications for policy-making in individual countries, as market-based decarbonisation policies may need to become much more stringent to overcome the loss aversion effect.

2. Methods

2.1. Loss aversion as part of prospect theory

The concept of loss aversion originates in the seminal work by Kahneman and Tversky [18]. Their research presents empirical evidence for systematic violations of classical utility theory in decision-making of people, and proposes Prospect Theory as a descriptive framework which is consistent with such observations [for a comprehensive review, see 45]. As a positive theory of choice, it aims at describing how people actually behave (as observed empirically). This theory contrasts with the standard normative nature of utility and rational choice theory, which describe how people ought to behave, if they were acting according to a set of pre-defined theoretical axioms (constituting the 'economic man' of economic analysis) [46].

While the initial formulation of Prospect Theory focused on describing risky choices between probabilistic payoffs (such as playing the lottery) [18], the framework was soon extended to choices between consumption goods which differ in attributes [9,20]. Centrally, such choices are found to be reference-dependent and subject to loss aversion, relative to the decision-maker's subjective reference point.

Reference dependence reflects experimental evidence that people do not derive utility from absolute levels of wealth or pleasure (as in classical utility theory), but from changes relative to a reference point (usually the status quo). As illustrated in Fig. 1, positive changes are evaluated as gains, and negative changes as losses. The fundamental reasoning behind reference dependence is derived from the psychology of sensual perceptions (such as seeing or feeling), which are more sensitive towards changes in the external environment (such as in brightness or temperature) than towards their absolute levels [7]. For example, most people can only identify relative differences in sound frequencies, and are unable to name absolute sound frequencies without external reference [47].

Loss aversion describes the empirical observation that peoples' choices are more sensitive to losses than to gains, relative to their subjective reference points. Even when both are of the same absolute magnitude (e.g., in monetary terms), they are perceived and valued differently in the process of subjective decision-making. In early experiments, it was estimated that the relative impact of losses on choices is 2.25 times stronger, which is taken as an empirical measure of the degree of loss aversion [19]. In an experiment on car choice, Gaechter et al. [48] estimate that 88% of participants are loss-averse, with an interquartile range for the loss aversion coefficient of 1.3–3.0.

Due to reference-dependent loss aversion, a move away from the reference point towards an alternative is perceived as relatively unattractive, even if gains are two times larger in objective magnitude than losses. As a result, people perceive deviations from their current situation as less attractive than what rational choice theory would imply, and therefore show stronger than expected preferences for the status quo and their current entitlements — referred to as 'status quo bias' and 'endowment effect' [9,49]. Importantly, the asymmetric effect of loss aversion is conceptually different from behavioural time preferences (discount rates), which may lead to a systematic undervaluation of future cost savings: discount rates are applied to all losses and gains,

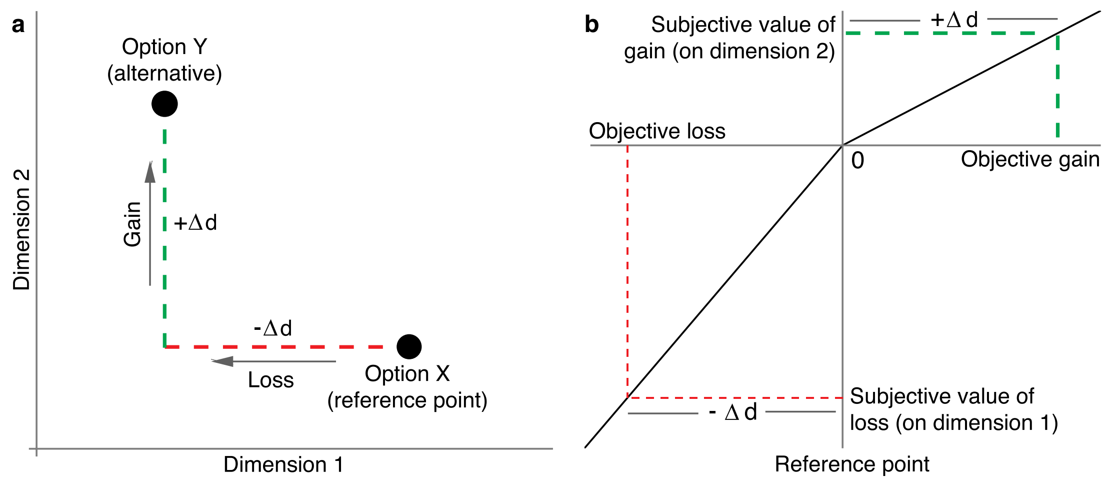

Fig. 1. Reference-dependence and loss aversion in product choice.(a) In a riskless choice between two consumption goods (options X and Y), losses and gains correspond to differences in their individual attributes (dimensions 1 and 2), relative to the reference point. Switching from option X to Y implies a loss in dimension 1 ($-\Delta d$, shown in red), and a parallel gain in dimension 2 ($+\Delta d$, shown in green). **(b)** Losses and gains are evaluated according to the empirically derived Prospect Theory value function. In case of loss aversion, losses are assigned a larger subjective decision value than gains. Even if both are equal in absolute objective magnitude (e.g., monetary value), switching to the alternative option would thus be perceived as unattractive. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

irrespective of any reference point.[1]

2.2. Modelling loss aversion in energy technology choices

The starting point of our work is the generalised reference-dependent model of consumer choice by Tversky and Kahneman [20], which we adapt to energy technology choices by consumers. Conceptually, our model considers a choice between two technology options (i and j) that differ on two or more valued dimensions (d) (see Fig. 1a). When comparing technologies i and j, we denote the implied difference on each dimension relative to the reference point as $\Delta d_{x,i\to j} = d_{x,j} - d_{x,i}$, where x is the dimension, i the reference point and j the alternative option. Each difference is evaluated as a loss or gain (i.e., as a relative disadvantage or advantage), relative to the reference point. The value of each loss or gain, $v(\Delta d_{x,i\to j})$, is determined by a two-part value function of the form

$$v(\Delta d_{x,i\to j}) = \begin{cases} \Delta d_{x,i\to j} & \text{if} \quad \Delta d_{x,i\to j} \geq 0 \\ \Delta d_{x,i\to j} * \lambda & \text{if} \quad \Delta d_{x,i\to j} < 0 \end{cases} \tag{1}$$

where λ is the coefficient of loss aversion. We denote the overall evaluation of choice option j from reference point i as $v(i\to j)$, which equals the sum of evaluated differences over all dimensions x (such as upfront costs and energy costs):

$$v(i\to j) = \sum_x v(\Delta d_{x,i\to j}) \tag{2}$$

For $\lambda = 1$, the model yields the classical rational choice model of economic theory. For $\lambda > 1$, however, the evaluation of choice options becomes asymmetric: due to loss aversion, any difference on a dimension has a greater impact on choices when it is evaluated as a loss, and a shift in the reference point can lead to a reversal of preferences (as losses can turn into gains). For the loss aversion specification of the model, we use a default parameterisation of $\lambda = 2.25$ [based on the original experiments by 20], and analyse the sensitivity of results for a range of λ between 1 and 3 [based on 48].[2]

As an example, suppose that a person needs to replace a heating system, and that preferences for this choice are determined by two dimensions (d_1 and d_2): upfront capital cost (i.e., the purchase price and eventual installation costs), and the (discounted) total operating costs during a technology's lifetime.[3] Without loss aversion ($\lambda = 1$), choices are straightforward: When one technology has lower total costs, it should be strictly preferred. When total costs of both technology options are identical, any objective decision-maker should be indifferent between both options. Preferences should not depend on the technology which is being replaced.

With loss aversion ($\lambda > 1$), preferences depend on the decision-maker's subjective reference point, which is potentially ambiguous [and remains uninterpreted in 20]. We adopt here the interpretation of the current endowment hypothesis, which intuitively assumes that an individual's reference point is their currently owned bundle of goods [50], so the currently owned technology in our specific case. Due to loss aversion, relative disadvantages of an option (*losses*) now loom larger than relative advantages (*gains*). This suggests a relatively stronger preference for the status quo technology, compared to preferences without loss aversion — even if both technologies are identical in overall costs. It is sufficient if they differ in their underlying dimensions.

Technology adoption within a larger population depends on the distributed decisions of heterogenous people, who act in different contexts and can have different perceptions of the available options. Similarly, technologies and their cost dimensions are subject to variation. For example, when considering the choice between a gas-fired heating

[1] Although loss aversion and discounting are conceptually different, they can thus lead to similar patterns in empirical data on decision-making, such as the typically observed relatively larger impact of upfront costs on energy technology choices. When loss aversion is not considered, empirically estimated discount rates are therefore likely to be biased upwards, as they also capture the (reference-dependent) effect of loss aversion. Disentangling empirical estimates of time preferences/discount rates from the influence of loss aversion is possible, but requires richer datasets [for an example, see [33].

[2] Note that for 5% of individuals, the estimated degree of loss aversion is negative ($\lambda < 1$), which implies a larger sensitivity to gains than to losses [48]. However, the average degree of loss aversion is highly unlikely to be negative within larger groups, so that the (hypothetical) case of $\lambda < 1$ is not considered here.

[3] Note that it remains debated in the literature whether loss aversion applies to price and quality dimensions in the same way [50]. For the case of product choices, a review by Neumann and Boeckenholt [21] finds no evidence that consumers show lower loss aversion for price dimensions, relative to quality dimensions (based on a meta-analysis of 109 effect observations).

system and an electric heat pump, both technology options exist in various different configurations, and may have different cost characteristics in different contexts (such as different climatic or building conditions). For representing such diversity, we extend the model to the case of a heterogenous population, making technology choices over time [based on 11,51].

Within each simulation period t, we calculate the fraction of the population which would prefer technology j over technology i. This fraction is denoted as $F_{i\rightarrow j,t}$, and equals

$$F_{i\rightarrow j,t} = S_{i,t-1} * P[v_t(i\rightarrow j) > 0]. \tag{3}$$

$S_{i,t-1}$ is the market share of technology i in the previous period, which is taken as a proxy for the share of the population for which technology i is their current reference point. $P[v_t(i\rightarrow j) > 0]$ is the probability that switching from technology i to j is seen as attractive in the current period, based on the distributions of evaluated differences in technology dimensions.

2.3. Modelling heating technology choices

As a case study, we proceed by implementing the reference-dependent model of technology choice into a bottom-up model of technology diffusion in the residential heating sector, FTT:Heat [for a full model description and further details, see 51,52]. The sector is well-suited for studying the impact of loss aversion on technology uptake: Decisions are (overwhelmingly) made by consumers, but not predominantly influenced by other interfering cultural factors (such as status consideration in mobility) [53,54].[4] At the same time, together with passenger road transport, the sector accounts for the largest share of direct GHG emissions by households [55].

FTT:Heat simulates the uptake and replacement of 13 different heating technologies in 59 world regions covering the globe, up until 2050, from a bottom-up perspective: under given behavioural assumptions, which technologies would households prefer, and how fast can new technologies grow within the market? As a simulation model, it is thus particularly well suited to integrate real-world imperfections of human decision-making, such as loss aversion. As part of the integrated assessment model E3ME-FTT-GENIE, it is linked to models of the power sector, wider economy and climate [56,57].

Fig. 2 presents a schematic overview of the central model components of FTT:Heat, and how loss aversion is added to the model's decision-making core. The exogenous model driver is the projected annual demand for heat as an energy service. For each individual region, this demand depends on assumptions regarding future levels of population growth, household income and the thermal insulation of houses [as described in 51].

At the heart of FTT:Heat, in each simulation step (set to three months) it is simulated which technologies are chosen by households to fulfil their demand for space and water heating, if they were to buy or replace a heating system in this period. Technology choices are determined by a pairwise comparison of all available technology options, based on distributed costs parameters[5]: upfront investment costs, operating costs (energy costs plus maintenance-repair costs), and an empirically calibrated 'intangible' cost component. The latter represents technology characteristics which are valued by households (such as convenience or co-benefits), but not captured by the engineering-based cost data [for a description of the methodology, see 51]. As a representation of heterogeneity, investment and operating costs are distributed around their mean values [for the detailed data, see 51,52]. All cost values are normalised to the generation of one unit of useful heat, and future operating costs are discounted [by a rate of 9%, based on 64]. Upfront investment costs are subject to endogenous future cost decreases, as a function of each technology's cumulatively installed capacity ['learning by doing', with cost reductions between 10 and 30% for every additional doubling of the cumulative capacity, based on 65], which makes the model highly path-dependent.

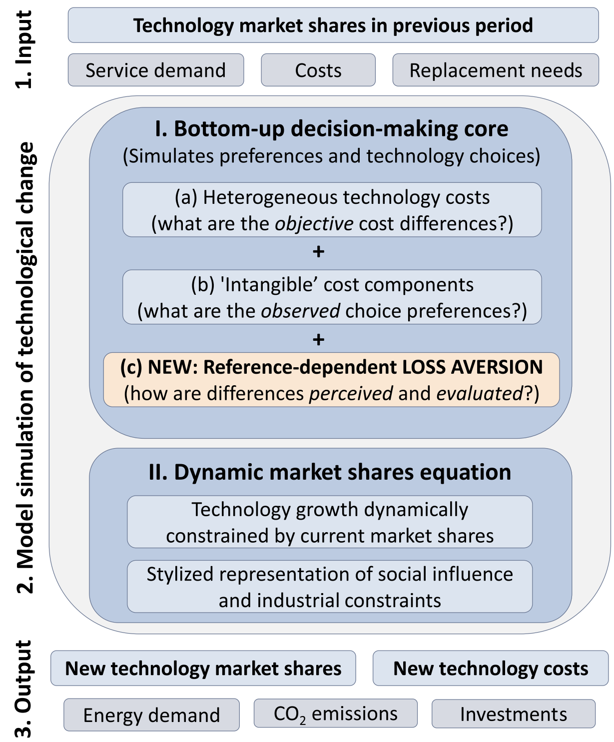

Fig. 2. Integration of loss aversion into the FTT:Heat model. The decision-making core of FTT:Heat simulates technology choices by heterogenous households from a bottom-up perspective. Technology choices by households are based on distributed technology costs and empirically estimated 'intangible' cost components. In the new model specification, reference-dependent loss aversion is added to the decision-making core, in order to simulate more realistically how differences between technologies are subjectively perceived and evaluated by households.

In the original model specification, available technology options are compared to each other without consideration of a reference point, simply be evaluating symmetric cost distributions. Formally, pairwise comparisons take the form of binary logits in which the relative frequency of choices happening is weighted by their existing level of popularity, which generates S-shaped evolutionary diffusion curves endogenously [66,67].

For the inclusion of loss aversion, we have added the reference-dependent model from Section 2.2 to the original decision-making core of FTT:Heat. For this purpose, the loss aversion model from Section 2.1 (Eq. (1)–(3)) is extended from two to thirteen choice options, which are compared to each other on three dimensions. If the coefficient of loss-aversion in Eq. (1) is set to $\lambda = 1$, the new decision-making core of FTT:Heat yields the same results as its original version, in which the comparison of considered options remains tied to the assumptions of (bounded) rationality. This allows an easy comparison of model results under alternative assumptions on decision-making, with and without loss aversion.

Loss aversion is implemented into FTT:Heat in the following way: First, in each simulation step (set to three months) and for each region, the model estimates the perceived value of potential losses and gains

[4] This is not supposed to imply that technology choices in residential heating are unrelated to social or cultural factors.

[5] Technology cost data are taken from [58–62]. Residential fuel prices are based on [63]. More details on the data and assumptions are given in previous publications, see [51,52].

from technology switching, $v(\Delta d_{x,i\to j})$, for any possible pair of technologies, based on Eq. (1). For the case of heating technologies, it is assumed that losses and gains can result from three dimensions: upfront investment costs, operating costs, and the 'intangible' cost component. As in the original model specification, investment and operating costs are distributed around their mean values, as a representation of heterogeneity. For any possible pair of heating technologies, the distribution of losses and gains is estimated by means of a Monte Carlo simulation.[6]

Second, for each comparison of two technology options, the overall attractiveness of technology switching, $v(i\to j)$, is estimated as the sum of individual losses and gains over all considered dimensions, according to Eq. (2).

Third, choice preferences $F_{i\to j,t}$ are estimated for each possible combination of technologies, based on Eq. (3) and the distributions of evaluated losses and gains. The distribution of reference points is taken to be the market shares of technologies in the previous period ($S_{i,t-1}$), in each respective region.[7]

Last but not least, we derive the substitution of market shares from heating technology i to j in period Δt, as:

$$\Delta S_{i\to j} = F_{i\to j,t}\tau_i^{-1}S_{i,t-1}S_{j,t-1}\Delta t \tag{4}$$

τ_i is the average expected lifetime of technology i. Combined with the market share of i in the previous period ($S_{i,t-1}$), it is used to approximate the fraction of technology i which needs to be replaced. The rate of substitutions is dynamically constrained by technology j's market share in the previous period, as a stylised representation of limited production capacities on part of industry and limited information on part of households [67,68]. In addition, it is assumed that households do not switch back to technologies with a much lower comfort level, i.e. that households with modern heating systems (such as district heat, gas, electricity) do not choose coal or traditional biomass [following 69].

Since preferences are diverse, we calculate substitutions in both directions, to determine the net substitution from technology i to technology j. The sum of all such pair-wise comparisons over all technologies yields the cumulative net change in market shares of technology j:

$$\Delta S_{j,t} = \sum_i S_{i,t-1}S_{j,t-1}\left(F_{i\to j}\tau_i^{-1} - F_{j\to i}\tau_j^{-1}\right)\Delta t \tag{5}$$

Formula 5 is the non-linear dynamic shares equation, conceptually similar to the modelling of imitation dynamics in evolutionary game theory [70].

In addition to regular end-of-lifetime replacements, households have the option to replace their existing functioning heating system prematurely. Based on economic considerations, this can be beneficial if the marginal running costs of operating the current system exceed the full costs of buying and operating an alternative technology. It is known that empirically, households only consider such a premature replacement if the potential savings exceed the initial investment in a limited period of time, usually around three years [71]. The original model specification of FTT:Heat is therefore based on such a behavioural payback threshold, as an approximation of observed real-world choices. However, such behaviour may at least partly be attributable to loss aversion. Therefore, here we assume that households apply the same type of rationality as for regular replacements, and apply the same discount rate (assuming a rate of 9%, the equivalent payback threshold is around 9 years). This means that the inclusion of loss aversion makes the model representation of premature replacements simpler (compared to the original specification), as a separate behavioural payback threshold is not needed any longer.

2.4. Policy scenarios

For demonstrating the modified version of FTT:Heat and the relevance of loss aversion, we simulate as an example a current trends scenario and four policy scenarios, all aiming at a decarbonisation of residential heating [based on previous work, see 51]:

- **Scenario a** projects the *current technological trajectory* into the future. It implicitly considers existing policies (the impact of which on technology preferences is implicitly captured by the 'intangible' cost components, which were empirically derived from recent diffusion data), but does not introduce new policies.
- **Scenarios b and c** simulate a residential *carbon tax* of 100 €/tCO_2 and 200 €/tCO_2, respectively, which is added to the household price of fossil fuels from 2020 onwards.
- **Scenario d** simulates a *technology subsidy* of 50%, which is paid on the upfront investment costs of heat pumps, solar thermal and modern biomass systems from 2020 onwards.
- **Scenario e** simulates the combined effect of the 100 €/tCO_2 *carbon tax* and the *technology subsidy*.

For the purpose of this analysis, it is assumed that the same policy instruments are implemented in all 59 simulated world regions. This is done for comparing global emissions changes with and without loss aversion, as an easy reference for the full climate change impact that loss aversion could have. It does not imply that such a global implementation of policy instruments is in fact preferable, or that all countries should implement the same policies.

In the 'current technological trajectory' and all policy scenarios, we assume a parallel decarbonisation of the power sector which is consistent with limiting global warming to 1.5 °C, as described in [51,72]. This reduces the projected indirect emissions of heating with electricity-based technologies, independently of any developments in the residential heating sector.

When a carbon tax is introduced, the tax increases the energy costs of fossil fuel technologies. According on local energy prices, the policy is designed to make renewables competitive in terms of overall costs. However, parity in total costs does not change the fact that both technology groups can have reversed cost dimensions: while the carbon tax further increases the relative advantage of low-carbon technologies in terms of operating costs, the policy does not reduce their relative disadvantage in terms of higher upfront investment costs. Because losses loom larger than gains for loss-averse decision-makers, a relatively stronger change in relative energy costs should be necessary for obtaining the same effect on technology uptake as it would be projected without loss aversion. If the coefficient of loss aversion is around two (as in our assumptions), it should therefore be expected that the carbon tax under loss aversion would need to be around twice as high, for obtaining the same impact on technology diffusion as under rational decision-making without loss aversion. For the same reason, upfront subsidies should be relatively more effective in impacting technology choices than a carbon tax: a carbon tax increases the size of relative gains from switching to renewables (in form of energy cost reductions), while the subsidy reduces the size of relative losses, which are valued by the loss aversion coefficient.

3. Results

3.1. Simulation results at the global level

Fig. 3 shows the projected global heat generation by technology type

[6] Due to the asymmetric nature of reference-dependent loss aversion, the sampling of choice distributions by means of numerical Monte Carlo simulations is conceptually more straightforward than to find an analytical representation of probability distributions.

[7] For each individual region, historic technology market shares were compiled from data on final energy demand by households (grouped by fuel type), combined with data on the stock and sales of different heating technologies [for a detailed description of the database, see [51,52].

and resulting CO_2 emissions (direct emissions plus indirect emissions from electricity generation) for scenarios a-e, with and without loss aversion. The corresponding differences in technology market shares can be seen in Fig. 4, for 2015 (the start of the simulation) and 2050. Fig. 5 shows these differences for a range of loss aversion coefficients, in comparison to the effect of different discount rates.

In all scenarios, the projected diffusion of renewable and highly efficient heating technologies (solar thermal, modern biomass and heat pumps; renewables from hereon) is much faster under decision-making without accounting for loss aversion, compared to the model specification with loss aversion. At the start of the simulation in 2015, renewables have a global market share of 9%. Until 2050, under the current technological trajectory without additional policies, this share is projected to autonomously increase to 39% without loss aversion (for details, see 51), but this declines to 22% when loss aversion is included. In other words, not considering loss aversion in the behavioural assumptions overestimates the baseline uptake of renewables by around 80% on the global level.

In both model specifications, the carbon tax and the subsidy are projected to increase the uptake of renewables, relative to current trends. However, not considering loss aversion in the model overestimates the policy impact considerably: projected global market shares of renewables in 2050 are around 6–18% points higher, compared to the model specification with loss aversion (see Fig. 4). Consistent with our expectations, differences in the projected uptake of renewables are smaller for more stringent policy scenarios. While the model specification without loss aversion would project a 56% larger diffusion of renewables for a carbon tax of 100 €/tCO_2, the relative gap is reduced to

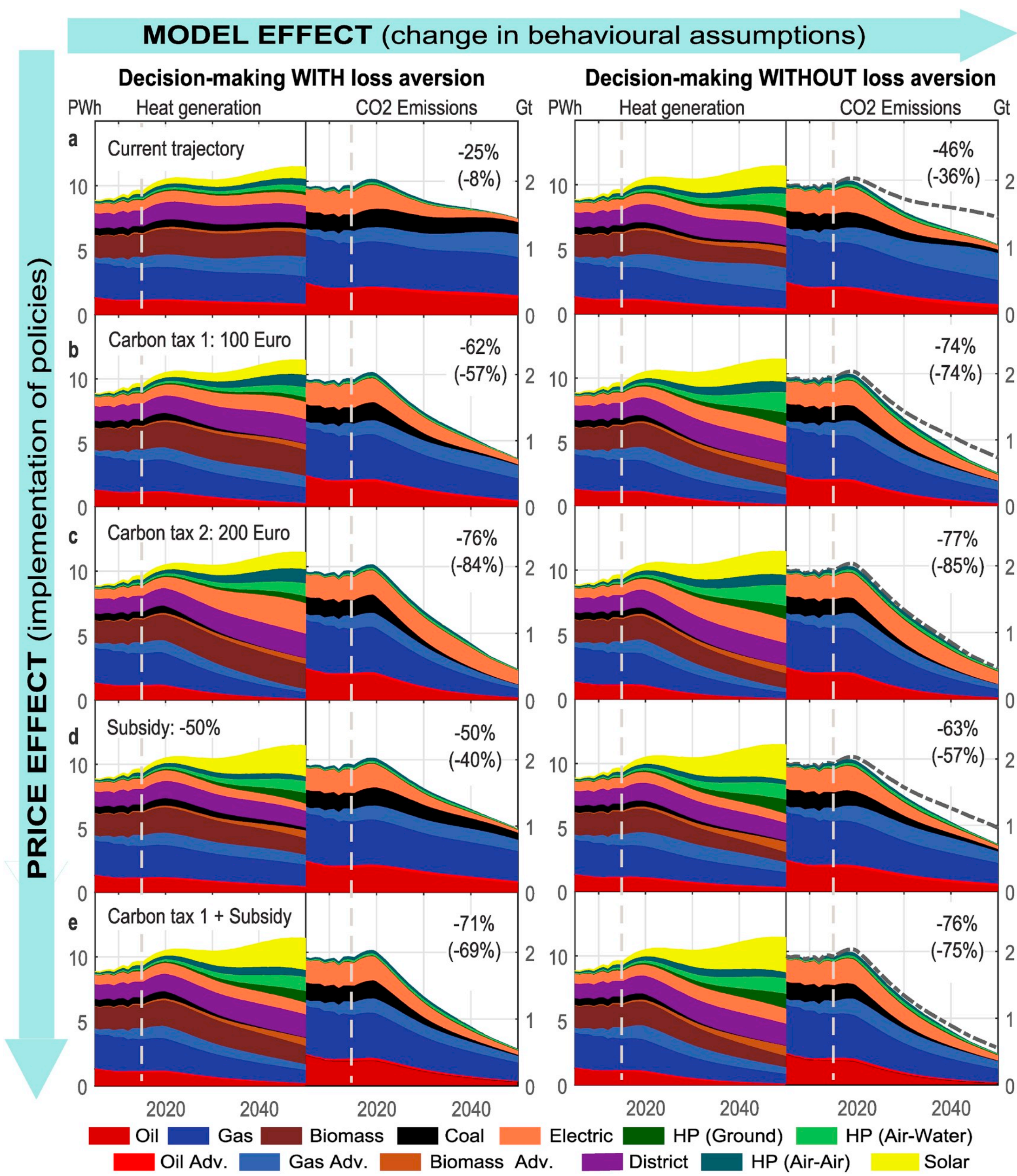

Fig. 3. Global heat generation by technology and resulting CO_2 emissions. Direct and indirect CO_2 emissions (from electricity generation) from 2005 to 2050, under the current technological trajectory (a) and in three policy scenarios (b–e), as simulated by FTT:Heat. Panels on the left show the simulation results for decision-making which is subject to loss aversion, panels on the right for decision-making without loss aversion. Vertical lines indicate the start of the model simulation in 2015. Percentage values refer to the change in total CO_2 emissions in 2050, relative to their level in 2015 (values in brackets refer to direct CO_2 emissions only). In the right panels, dashed lines indicate the level of CO_2 emissions as simulated under loss aversion.

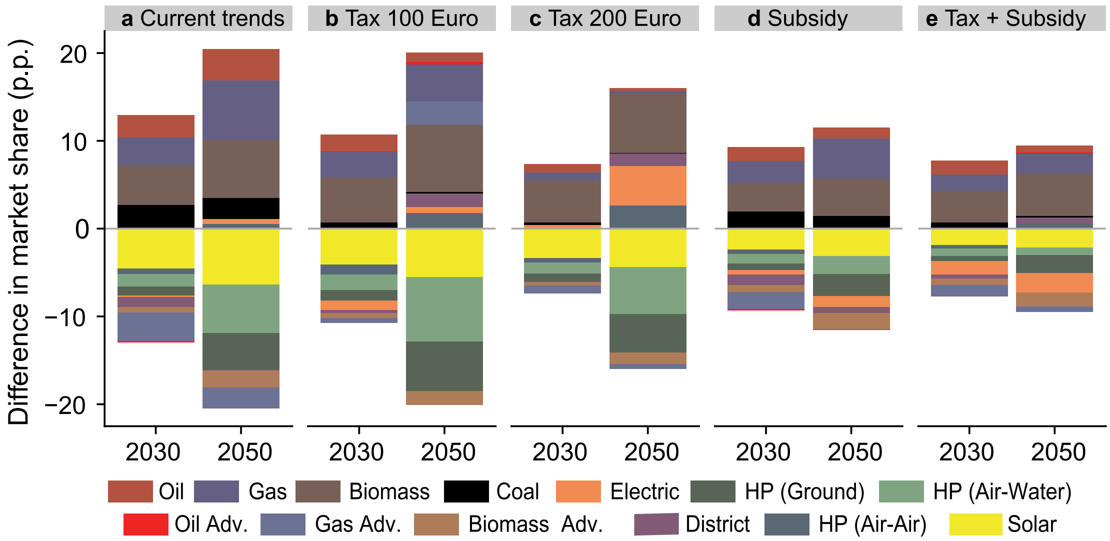

Fig. 4. Projected differences in global market shares of heating technologies. Stacked bars show the differences in market shares (measured in percentage points, p.p.) that would result from loss aversion in the model, relative to the model specification without loss aversion. Differences are shown for 2030 and 2050, under the current technological trajectory (a) and in four policy scenarios (b–e).

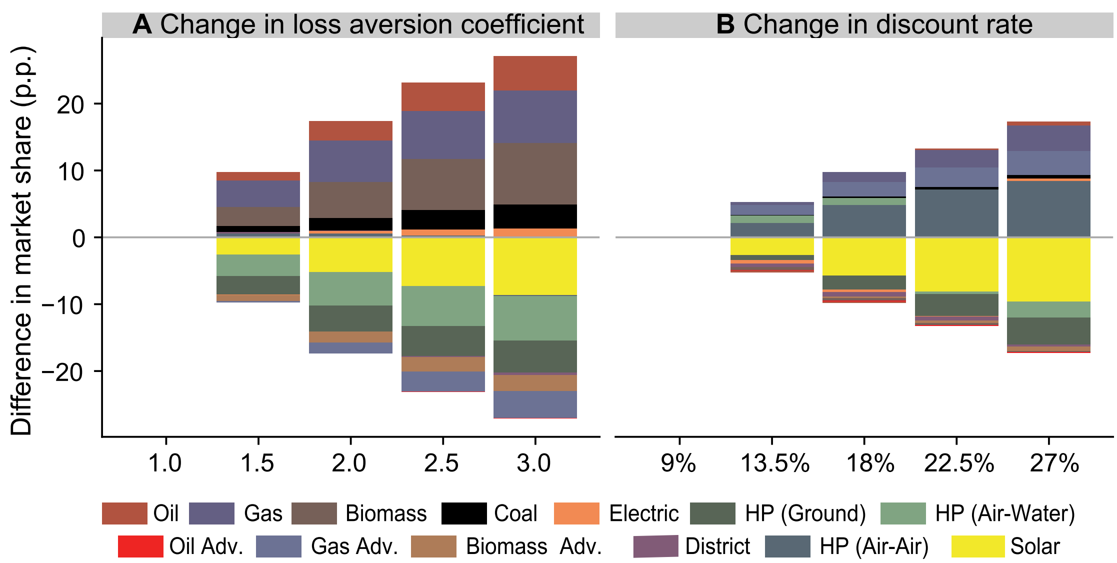

Fig. 5. Sensitivity of market shares in 2050 towards loss aversion and discounting. Stacked bars show the differences in projected market shares for 2050 in the 'current technological trajectory' (measured in percentage points, p.p.) that would result from different degrees of loss aversion (A), and different discount rates (B). All differences are relative to the model specification without loss aversion ($\lambda = 1$) and a discount rate of 9%.

33% for a carbon tax of 200 €/tCO_2, and to 21% for an upfront subsidy for renewables. This suggests that subsidies are indeed a more effective way for bridging the gap between the technology compositions with and without loss aversion (see Fig. 4). In case of very strong policy incentives, the resulting cost differences between technologies become so large that they eventually start to dominate the influence of loss aversion on choices, and households prefer the cheapest option despite their bias towards status-quo technologies. When the carbon tax is combined with upfront subsidies, for example, the relative gap between the projected market shares of renewables in both model specifications is reduced to 12%.

The projected differences in technology uptake directly impact levels of CO_2 emissions by residential heating (see Fig. 3). Under current trends, including decarbonisation of the power sector, annual emissions are projected to decrease by 25% until 2050 when assuming loss aversion in the decision-making, compared to 46% without loss aversion. With loss aversion, a carbon tax of 200 €/tCO_2 leads to similar reductions in total emission levels (−76%) than a carbon tax of 100 €/tCO_2 without loss aversion (−74%). From that perspective, it appears indeed to be an approximately correct rule of thumb that in this model, when the coefficient of loss aversion is around two, the same reductions in overall emissions are obtained with policy incentives twice as stringent. Similar as for the underlying trends of technology diffusion, the difference between both model specifications decreases with the stringency of the policy instruments. For example, the 200 €/tCO_2 carbon tax leads to comparable reductions in total emission levels with and without loss aversion (−76% and −77%, see Fig. 3).[8]

Even when the resulting emission reductions are almost identical

[8] Note that beyond a certain level, the marginal impact of additional policy incentives on technology diffusion is limited by the inertia of the technological system, foremost the physical turnover rate of heating systems (which have an average assumed technical lifetime of 20 years).

(like in scenarios c and e), the underlying technology mix remains substantially different in its composition, as different types of low-carbon technologies are preferred with and without the model representation of loss aversion in the decision-making (see Fig. 4). In case of the 200 €/tCO_2 carbon tax, for example, both model specifications result in very similar overall market shares of fossil fuel technologies in 2050. However, even given a similar degree of decarbonisation, there remain large differences in low-carbon technology market shares. With loss aversion, there is a much larger reliance on low-carbon technologies with larger market shares at the start of the simulation, such as traditional biomass, district heating, or direct electric heating. Without loss aversion, in contrast, there is a relatively larger market penetration of relatively newer technologies such as heat pumps and solar, which only have small market shares in 2015. As these technologies also tend to be relatively more efficient, the model specification without loss aversion underestimates global annual net expenses on heating (upfront plus running costs, excluding carbon tax payments) in 2050 by around 13% (in scenario c), compared to the projections without loss aversion.

The projected changes in technology choices due to loss aversion are substantially different from the changes that result from an adjustment of the discount rate in the model, as can be seen in Fig. 5. When the discount rate is increased, the relative importance of future energy costs decreases, which implies a shift of household choices towards technologies with relatively lower upfront costs. Higher degrees of loss aversion, on the other hand, imply a 'conservative shift' of household choices towards technologies with relatively larger market shares, independently of the relative importance of upfront and future energy costs. For example, increasing the loss aversion coefficient leads to a higher market penetration of biomass and fossil-fuel based heating systems (including oil and coal), at the expense of all types of low-carbon technologies. Increasing the discount rate, on the other hand, leads to a shift of market shares within the group of renewables, towards relatively less capital-intensive low-carbon technologies (e.g., air-source heat pumps instead of solar thermal systems).

3.2. Simulation results for selected countries

The effects of loss aversion on projected technology uptake is further illustrated at the example of individual countries, as shown in Fig. 6 for the cases of Germany, Ireland, Korea, Spain, and the USA. These five countries were chosen to represent different historical technology compositions in the residential heating sector, which allows to analyse the influence of loss aversion under different regional contexts.

In Germany and the USA, the overall shares of fossil and renewable technologies are more or less the same under both model specifications. Despite this, there remain substantial differences in terms of individual technology shares. Within the group of fossil technologies, advanced (i.e., more efficient) variants of gas and oil boilers diffuse faster without loss aversion. Similarly, within the group of renewable technologies, not considering loss aversion results in a larger projected uptake of (relatively more efficient) ground-source and (relatively more expensive) air-water heat pumps, relative to the cheaper variant of air-air heat pumps (and also larger shares of direct electric heating).

Differences under the 'current technological trajectory' are more obvious in case of Ireland, Korea and Spain. In Ireland, coal keeps playing an important role in the heating market until 2050 with loss aversion, while it is largely replaced by advanced biomass systems without loss aversion. Both in Ireland and Korea, renewables hardly see any growth with loss aversion, but are projected to replace substantial capacities of oil heating systems without loss aversion. In Spain, the market share of solar thermal is projected to increase substantially in both model specifications, but is more than twice as large without loss aversion. Importantly, in all cases the model projections are almost identical to each other at the beginning of the simulation: it is only over time that the differences from loss aversion gain a visible impact, eventually accumulate and become path-dependent.

In each country, the respective effect of loss aversion foremost depends on the observed technology market shares at the start of the simulation. The initial market shares in each country determine how many consumers consider a certain heating technology as their 'status quo' option. In direct comparison of two technologies, the 'status quo' technology always has a relative advantage due to loss aversion. In practice, this means that loss aversion favours the selection of more traditional technologies, such as gas or electric resistance heating, which currently are the 'status quo' in many households. For the same reason, the attractiveness of switching to relatively newer alternatives, such as heat pumps, is relatively lower under loss aversion. As a result, under loss aversion, switching between any pair of technologies becomes much more unlikely, and the technology composition is more likely to remain as it is.

The pattern of differences between model specifications with and without loss aversion persists when the effect of a carbon tax (100 €/tCO_2) is simulated. In both cases the policy increases the share of renewables in all five countries, relative to the 'current technological trajectory'. However, as on the global level, the projected share of renewables is larger in the model specification without loss aversion. Also, the model projections differ substantially with regard to the degree of decarbonisation, and the technology pathway that leads to this decarbonisation: In all five countries, market shares of fossil technologies in 2050 are projected to be lower without loss aversion. Furthermore, more efficient and capital-intensive variants of renewable technologies tend to be chosen when loss aversion is not considered. The latter is perhaps most striking in case of Spain, where the portfolio of renewables becomes dominated by (relatively cheap) air-air heat pumps under decision-making with loss aversion, and by (relatively capital-intensive) solar thermal installations without loss aversion.

4. Discussion

4.1. Impact of loss aversion on technology uptake

The different projections of technology uptake with and without loss aversion can be traced back to the asymmetric valuation of losses and gains under reference-dependent decision-making. Based on the technology assumptions in FTT:Heat, renewable heating technologies have relatively higher upfront costs (compared to fossil fuel-based systems), but also a relatively higher degree of energy efficiency. Prospect Theory suggests that due to loss aversion, the relative disadvantage (loss) of higher upfront costs has a relatively stronger impact on decisions than the advantage in energy costs (gain), when evaluated from the reference point of fossil-fuel technologies. Importantly, the effect of loss aversion on choices is asymmetric, as the classification of gains and losses always depends on the reference point. For example, switching from a gas boiler to a heat pump is evaluated differently than switching from a heat pump to a gas boiler. Both situations imply different perspectives on what is perceived as gains and losses, and hence different evaluations of technology switching.

The expected influence of loss aversion on technology uptake can be interpreted as a manifestation of the 'status quo' [49]: People tend to prefer technologies which are already familiar to them, which increases the likelihood of choosing the 'status quo' option – even if it should, rationally, result in higher overall monetary costs from an engineering perspective. Accordingly, the projected trajectory of technology diffusion becomes subject to a 'conservative shift', in which future technology choices are more dependent on current market shares. This is reflected in the observation that technologies that have low market shares at the start of the simulation have a disadvantage, which happen to be the same technologies that have higher upfront costs (low-carbon technologies are capital-intensive).

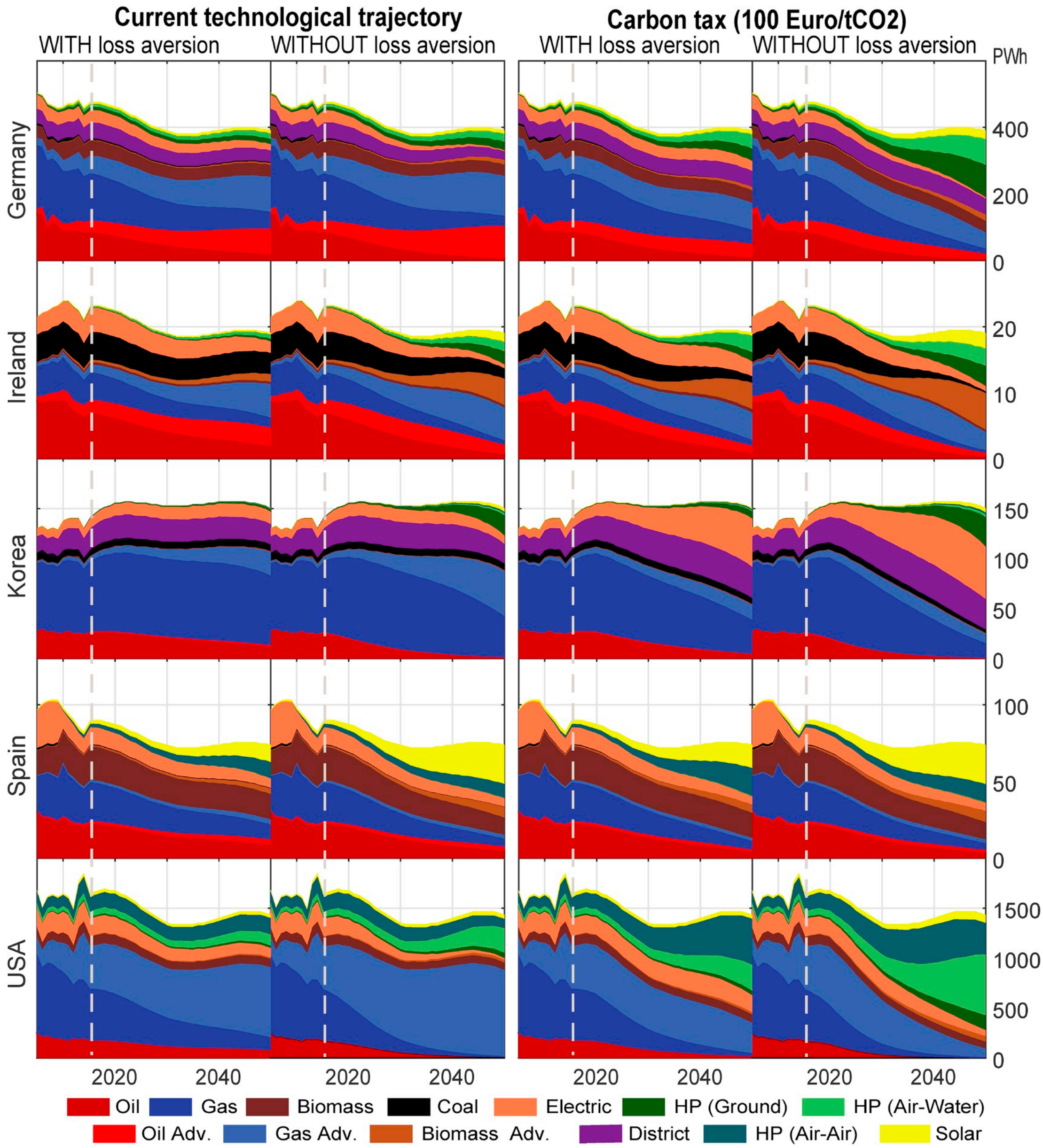

Fig. 6. Simulated heat generation by technology in five exemplarily chosen countries. Heat generation between 2005 and 2050, with and without consideration of loss aversion in the model. Panels on the left show the simulation results for the current technological trajectory, panels on the right for a carbon tax of 100 €/tCO_2. Vertical lines indicate the start of the model simulation in 2015.

4.2. Implications for the design of policies

In the context of climate change mitigation, policy incentives such as taxes and subsidies are typically meant to ensure that low-carbon technologies can financially compete with fossil-fuel technologies. However, loss aversion implies that competitiveness in overall costs is not always sufficient for achieving a market diffusion of new technologies, as perceived losses can have a relatively stronger impact on decisions. This implies that policies may need to become much more stringent to overcome the loss aversion effect, and that it may prove more effective for policies to aim at reducing relative disadvantages (*losses*, such as higher upfront costs via the payment of subsidies), than aiming at further increasing relative advantages (*gains*, such as lower energy costs). Furthermore, given the reported heterogeneity of loss version between people, policies could in principle be designed differently for different target groups, for example based on age or income [32]. This was not simulated here, and requires further research.

From the perspective of economic welfare analysis, loss aversion implies that technology choices of individual households can become inconsistent with their own long-term preferences, which can justify policy intervention [10]. Ideally, interventions should contribute to reduce the effect of loss aversion by providing information to people how it influences their decision-making. However, given that it is likely a deeply-wired pattern in human behaviour, it could be hard or even impossible to overcome on a fundamental cognitive level [30]. Most likely, it is therefore not possible to directly influence the degree of loss aversion of individuals. As an alternative, the design of information policies could take into account the influence of loss aversion on decision-making. For example, information campaigns could be framed in a way that not investing in renewable technologies becomes perceived as a loss, which households want to avoid. However, while this could be effective in theory, Nicolson et al. [35] report that loss-framed messages were not effective in the case of choosing electricity tariffs.

4.3. Implications for modelling

From the perspective of modelling, it is important to underline that the influence of loss aversion does not simply correspond to an undervaluation of future energy savings, as they would be captured by (behaviourally estimated) time preferences or discount rates. In both model specifications, discounting is applied to all gains and losses in the exact same way, depending on the year in which they occur. In contrast, loss aversion is only applied to subjectively perceived losses, depending on the reference point. A representation of loss aversion by an adjustment of cost attributes or discount rates would thus be inaccurate: it would ignore the dependence of choices on the current technology stock, and would instead lead to an overly simplistic preference-shift towards less capital-intensive technologies (as illustrated in Fig. 5).

Instead, loss aversion requires a different model representation of decision-making — not only for our example of heating systems, but potentially for all technology choices made by individuals (e.g., cars or electric appliances). Ideally, such representations are not limited to loss aversion, but could also include further empirical findings on decision-making, behavioural biases and their possible interactions (Shogren and Taylor [12] point out that 25 biases are relevant to economic decision-making, which implies 125 possible interaction effects between biases).

4.4. Limitations and uncertainties

Including loss aversion in models is a significant step forward in the context of positive modelling methods to appraise possible policy strategies. However, it remains unclear so far what causes loss aversion on a fundamental cognitive level. While the estimated loss aversion coefficient is around two on average, there is evidence for a considerable variation between product types and individuals. For example, relatively stronger loss aversion is found for durable product categories [for a meta-analysis, see 21]. Gaechter et al. [48] found that loss aversion increases with an individual's age, income and wealth, while higher education decreases loss aversion. It therefore remains uncertain what is the exact degree of loss aversion for the choice of different types of energy technologies, to which extent it differs between different consumers and countries, and how it depends on the context of decision-making. While we have assumed that loss aversion is identical around the globe, further research could also account for variations in loss aversion between countries and cultures [6,73].

More generally, one has to be careful with the generalisation of Prospect Theory to societal contexts that differ from those under which experiments were made. In particular, although loss aversion has been observed in a variety of contexts for individual decision-making, it remains unclear to which extent it also applies to groups of people, which is of interest for energy models and policy-making. It is arguably an oversimplifying generalisation that the group behaves like an individual, an assumption commonly made in economics with the use of the representative agent [74]. In reality, it is not clear that all agents evaluate choice options using similar reasoning, and to which degree agents influence each other [66,75]. While agents may exhibit loss aversion when facing choices individually, this effect could be weaker or stronger in social contexts.

From an anthropological perspective, decision-making can be seen under three different theoretical lenses [76]: (1) the *self-interested* (utilitarian) model, used in microeconomics, in which choices are directed by individual utility; (2) the *social* model in which decisions are made by social groups, and (3) the *moral* model in which agents make decisions according to beliefs, values, culture and tradition. The loss aversion concept belongs to the utilitarian paradigm, and makes no reference to group or cultural dynamics, which could in principle be stronger than individual utilitarian biases. Nevertheless, our results suggest clearly that despite omitting other possible group-related dynamics or cultural influences, the ex-ante evaluation of policy strategies could be much better informed if loss aversion is included in policy analyses.

Overall, the FTT:Heat model and its loss aversion component are based on the best available empirical knowledge about consumer decision-making. The model is based on a rich empirical data set of historical technology diffusion and the modelling of loss aversion is based on experiments from a wide range of decision-making contexts. Furthermore, its simulations for the near future are consistent with observed technology choices in the past [51,52]. Still, it remains an unsolved question how the model's projections of policy effectiveness can be validated for the (more distant) future, given that the model aims to simulate policy-induced technological change which has no direct precedence in human history. Ambitious decarbonisation policies are outside of what has so far been implemented in most countries, and little is known on how people react to these policies under real-world conditions. Furthermore, the context of technology choices in energy transitions is constantly evolving. This makes it inherently uncertain to which extent model structures and parameters remain valid in the (distant) future, or if they might need to be adjusted in the light of new developments. For example, will human decision-making on energy technologies at one point be supplemented by artificial intelligence, and how would this change the impact of behavioural biases such as loss aversion?

5. Conclusion

We started from the question how loss aversion can be included into a simulation-based energy model, and to which extent it influences model projections of technological change and the effectiveness of climate policies, both on the global level and on the level of individual countries. We find that the model representation of loss aversion is not only feasible, but also relevant. Its consideration substantially reduces the projected uptake of renewable and energy-efficient technologies, as well as the projected impact of market-based policy instruments.

On the level of individual decision-making, we have shown that loss aversion leads to stronger preferences for technologies that are already established in the market, and are therefore likely perceived as the subjective reference points of individual consumers. When comparing two technology options from a subjective reference point, loss aversion implies that relative disadvantages (*losses*) have a larger impact on decisions than relative advantages (*gains*). If consumers see higher upfront investment costs as a loss and future energy savings as a gain, this results in a relatively lower valuation of renewable and energy-efficient technologies. Even if they are seen as overall more attractive than fossil fuel technologies from an outside engineering perspective, consumers are more likely to stick with their current technology.

In our example of heating technology uptake, not considering loss aversion overestimates the global market shares of renewables in 2050 by up to 80% and underestimates future levels of residential CO_2 emissions by around 30%, compared to the improved model specification with loss aversion. Accordingly, loss aversion implies the need for much stronger policy instruments for achieving decarbonisation targets for residential heating: A carbon tax of 200 €/tCO_2 is projected to reduce overall emission levels to a similar extent than a carbon tax of 100 €/tCO_2 without the consideration of loss aversion. The differences are thus so large that the loss aversion effect influences outcomes as much as the policies, and policies may need to become around twice as stringent to overcome the loss aversion effect. In the absence of global policy regimes for the decarbonisation of energy end-use sectors, accounting for loss aversion is most relevant for policy-making on the level of individual countries or regions (such as the European Union), as we have illustrated for five exemplarily chosen countries.

More empirical research is required in order to better understand how loss aversion can help to explain the uptake pathways of different types of energy technologies, along with the question to which extent loss aversion differs between consumers and countries. In particular, it is important to improve our understanding of choice dynamics in different social and cultural contexts, making use both of controlled behavioural experiments and the evaluation of choices under real-world conditions. The consideration of such insights for energy modelling is still in its infancy, and more work is required on the integration of behavioural knowledge into simulation models of technology uptake.

In conclusion, our findings suggest that loss aversion has major implications for the modelling of energy technology uptake, as well as for the planning and ex-ante evaluation of policies, and warrant substantial further investigation.

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